

Article

# Understanding the Spatial Agglomeration of Participation in Agri-Environmental Schemes: The Case of the Tuscany Region

Fabio Bartolini \*  and Daniele Vergamini

Department of Agricultural, Food and Agro-Environmental Sciences, University of Pisa, Via del Boghetto 80, 56124 Pisa, Italy; daniele.vergamini@agr.unipi.it

\* Correspondence: fabio.bartolini@unipi.it

Received: 21 March 2019; Accepted: 9 May 2019; Published: 14 May 2019



**Abstract:** Agri-environmental schemes (AESs) constitute one of the main agricultural policy instruments that address environmental objectives in the Common Agricultural Policy. However, in spite of a 20-year application window and large budgetary shares allocated by EU member states, several studies demonstrate lower-than-expected environmental impacts. The reasons for poor environmental outcomes are the lack of targeting, low participation rates, spatial heterogeneity, and information asymmetry between farmers and public administrators. This study comprehensively analyses the determinants of AES adoption while highlighting patterns of the spatial agglomeration of participation in organic and integrated production. For this, we combine the results of farm-level adoption analysis with a spatial analysis of the participation rate. The results show that both micro- and meso-level characteristics strongly impact AES participation. In fact, farm and household structure, quality of extension services, and territorial conditions all significantly affect AES adoption.

**Keywords:** agri-environmental schemes; econometrics model; spatial econometrics; organic farming; integrated production; spatial agglomeration

## 1. Introduction

With the introduction of the MacSharry Reform in 1992, along with accompanying measures, agri-environmental schemes (AESs) have come to constitute the main policy instrument to address environmental objectives within the European Union's (EU's) Common Agricultural Policy (CAP). AESs offer compensation payments that aim to encourage farmers to adopt agricultural practices or prescriptions that positively affect environmental quality. Agri-environmental payments (AEPs) are designed, on average, to compensate minor income, and AES commitments help offset operational and transaction costs.

AESs have, for some time, been a major component of the Rural Development Policy (RDP) budget. Overall, a large proportion of the AES budget is allocated to driving the introduction or maintenance of organic and integrated production. In the new programming period (2014–2020), AESs—which are now called ‘agri-environmental climate schemes’—are now compulsory in all EU member states, with a minimum allocation of about 30% of the RDP budget. The AES objectives in the new programming period are: (a) Restoring, preserving, and enhancing biodiversity across the European landscape, including NATURA 2000 (According to the European legislator, the Natura 2000 areas define a network of protected natural areas in the EU) areas and high-value nature farming; (b) improving water management; (c) improving soil management; (d) reducing nitrous oxide and methane emissions from agriculture; and (e) fostering carbon sequestration in agriculture. The authors of [1] identify two criteria by which to support AESs—namely, ‘Does the practice offer clear environmental benefits?’

and ‘Would the practice likely be abandoned in the absence of AES support?’ These elements are not trivial, and they give room to research and investigate the efficiency and effectiveness of this policy mechanism, by allowing researchers to analyse the AES adoption process and its determinants.

Even after 20 years of application and a large share of expenditure allocated to AESs in national rural development budgets [2], evaluation reports and the scientific literature have determined that AESs have engendered lower-than-expected environmental impacts [3–5]. The economics literature points to poor targeting levels, low participation rates, the heterogeneity of compliance costs [6,7], the spatial distribution of participation, and the presence of information asymmetry between farmers and the government as the main reasons for unsatisfactory AES outcomes [8–10]. There have been a few recent attempts to investigate the relationship between the ‘management option uptake’ (i.e., the ways in which farmers access and participate in the scheme on a voluntary basis) and the ability of the scheme to deliver ecosystem services [11]; these studies conclude that the prescriptive nature of such programmes weakens the government’s ability to promote effective environmental change. Against this background, we argue that low targeting levels and uneven uptake distribution represent key sources of potential policy failure that erode the effectiveness of AES interventions [7,12].

Despite these issues being critical to the design of AESs that involve more farmers and cost-effectively enhance environmental outcomes, previous studies have investigated these aspects separately. Poor spatial targeting [7,12] occurs when a programme cannot discriminate among different farms, areas, and environmental vulnerabilities, and thus reflects a lack of targeting in areas where the environmental benefits would otherwise be higher. These approaches are often constrained by the presence of high transaction costs [13] incurred by additional data needs [5] and changes in administrative procedures (e.g., different zoning, or different eligibility criteria and priorities). Other studies, in a bid to overcome the main limitation of uniform policy instruments, focus merely on spatial heterogeneity. The authors of [6,9,14] find that heterogeneity in compliance costs affects mainly the distribution of participation and the farmers’ information rent, and so they presume that such heterogeneity in AES design and implementation and in related policy mechanisms can improve those programmes’ effectiveness and efficiency.

Unlike those studies that undertake only single-aim approaches, the current study aims to assess the determinants of farmer participation in AESs, while concurrently determining the effects of location and spatial spillover on the concentration of AES participation. This objective is pursued by jointly using farm choice model results concerning AES adoption and data from a spatial analysis of the AES participation rate in Tuscany, Italy. The first analysis is undertaken by applying a multinomial logit model to identify the main farm, farmer, and household (micro-level) characteristics that positively or negatively affect the probability of AES participation [15]. We then apply a second model to compare the previous results, using spatial analysis. The application of spatial analysis techniques allows us to detect spatial agglomeration patterns and correct model estimations, while pinpointing determinants at the territorial level (meso level). The current study focuses on the adoption of organic and integrated production as two alternative farming systems whose practitioners receive AEPs. These two alternative farming systems, while competing with conventional production modes, provide relatively better environmental benefits [16]. The data used in this study are drawn from the 2010 Tuscany census data, which are merged with the ARTEA (i.e., the Regional paying agency) database; the merged data contain participants in the years between 2007 and 2010, including both new applicants and participants under the previous programming cycle (i.e., carryover from the previous programming period).

This paper is structured as follows. First, Section 2 reviews the literature concerning AES participation. Section 3 outlines the methodology of the current study, and Section 4 discusses the data used herein. Section 5 presents our results and provides a discussion. Finally, the paper ends with a conclusion in Section 6.

## 2. Determinants of AES Participation

The seminal work of [17] stresses the motivations and incentive mechanisms that drive AES participation. They describe four categories of behaviour that occur in advance of adopting environmental management practices—namely, those that act as active adopters, passive adopters, conditional non-adopters, and reluctant adopters. They then identify motivation, payments, and information as the main determinants among those categories. Similarly, [18], leveraging post-productivism farm pathways, identifies the adoption of multifunctional practices.

The agri-economic literature highlights the positive effects of incentive mechanisms in increasing farmer participation [19,20]. These works point out the significant effects that farm, farmer, and household characteristics have as determinants of AES uptake.

Another stream of research highlights the relevance of market and climate-condition uncertainties as drivers of AES adoption [21]. On account of risk-averse behaviour, farmers tend to prefer to receive lower, but certain payments (i.e., payments for adopting low or even unprofitable landscape measures, such as a 20-year land set-aside) rather than uncertain income, even if it were to be higher. A growing body of research examines the role of transaction costs and social capital as determinants of AES participation (see [22]); this branch of literature identifies trust and networking elements as central motivational factors that affect AES participation [15], along with the amount and quality of information available [23]. A relatively large number of studies focus on the threshold and transaction cost effects on participation (e.g., [24–26]). According to the results of these studies, young and well-educated farmers, as well as those with large farmlands and strong networking, are more likely to adopt AES, given the relatively lower transaction costs they could expect to incur. Many studies have examined farmer preferences in advance of new contracts pertaining to the provision of public goods. In this area, numerous studies apply the choice experiment model to analyse willingness to accept under a trade-off between AES commitments and payments (e.g., [26]). The authors of [27] apply a meta-analysis of the literature on the determinants of AES adoption and find that the few explanatory variables already used in the literature have only a small effect on the willingness to adopt. Meanwhile, in the literature, there is a conspicuous lack of a ‘social factor’ by which understanding could be improved.

From another perspective, there are studies that highlight the agglomeration effects of participation by looking at the effects of policy design on targeting and on social interaction among farmers. For example, [7,28] studied the spatial distribution of participation in measures 121 and 214 of the Emilia Romagna RDP, by using an alternative assumption vis-à-vis spatial regime. The authors of [29] analysed the spatial distribution of the share of organic farming in German municipalities and found that spatial spillover could explain participation agglomeration. The authors of [7,28,29] each found that priority-setting mechanisms and spatial differences in extension services affect participation in RDP measures. The authors of [30] derived similar results when looking at innovation diffusion: They point out that in terms of engendering participation, farmer networking and spatial interaction are much more important than interactions with agricultural extension officers.

These two last strands of the literature highlight the limits and potential of individual research approaches, as well as the elements critical to the successful application of AESs. However, to the best of our knowledge, no study has focused on combinations of two methods—an approach that could provide a balanced view of the effects of simple adoption (through the farm choice model) and the determinants of agglomeration. Such an integrated approach could provide evidence of the discrepancies among models (i.e., due to the presence of spatial spillover or to a selection mechanism implemented at the territorial level). In this way, the proposed research approach could enhance our understanding of the issues that relate to farmers’ adoption of AESs.

In the economics literature, the adoption of integrated or organic farming has been considered an investment decision problem. According to the model of [29], the selection of an alternative farming

system (e.g., integrated, conventional, or organic) can be framed in terms of an optimal investment choice during the time horizon,  $T$ ; this can formally be written as follows:

$$\left(-U_t(TCa^j) + \sum_0^T E[U_t(\pi_t^j - TCo_t^j) + Ua_t^j]e^{-rt}\right) - \sum_0^T E[U_t(\pi_{tco})]e^{-rt} > 0 \quad (1)$$

$$\pi_{tj} = \sum_{i=0}^I p_t^{ij} q_t^{ij}(v_t^{ij}, F) - c_t^{ij} v_t^{ij} + pay_t^{ij},$$

where:

$j = or; in$ , with  $or$  = organic and  $in$  = integrated production;

$TC_t^j$  = transaction costs of conversion, with  $a$  = ex ante  $TC$  and  $o$  = ongoing  $TC$ ;

$\pi_t^j$  = profit of a generic year,  $t$ , of the system,  $j$ ;

$U_t^j$  = utility of the system,  $j$ , for the year,  $t$ ;

$Ua_t^j$  = additional utility/disutility associated to the farming system,  $j$ ;

$p_t^{ij}$  = vector of output price of the  $i$  crops;

$q_t^{ij}$  = vector of produced quantities;

$v_t^{ij}$  = vector of input quantities;

$c_t^{ij}$  = variable cost of input;

$F$  = production factors (e.g., labour and land); and

$pay_t^{ij}$  = payment under AES.

Following [29], the equation contains some vectors—such as prices, costs, and spatially dependent production factors—that create spatial agglomeration among farming systems. Both climate condition and the diffusion of product-designed origin (PDO) can determine spatial agglomeration, on account of changes in cost, yield, and prices; however, the equation might return an uneven distribution of compliance costs in space. Moreover, one can assume that  $TC$  is affected by spatial agglomeration, given differences in extension services and institutional quality over space and differences in the networking capacities among farmers. Consequently, when analysing AES participation through the use of different analytical scales, models may return different explanatory variables.

### 3. Methodology

The current study looks to analyse both the adoption motivations behind, and the determinants of, participation in organic and integrated production schemes. It does so by combining the results of the adoption model with agglomeration analysis. In many studies, the linkages between farm choices and agglomeration are often addressed indirectly, as there are several interplays relating to the location, dominant farming systems, market opportunities, and the uneven distribution of agricultural advice and extension services, as well as different levels of efficiency among local institutions and trajectories of territorial development [7,31,32].

For example, location variables have been used in choice models as a proxy of the difference in demand for environmental services, or for participation costs; other studies that apply spatial analysis investigate the effects of spatial spillover and spatial autocorrelation in the disturbance term that derive from upscaling considerations and the dynamics of demand and supply, Marshallian externalities, or the creation of production districts (see [29,33]). The current study looks to discuss determinants by running two independent analyses and observing how the same set of determinants affects farm choices at the farm level, as well as agglomeration effects. The two analyses have been integrated into a two-stage method. In the first stage, we use a multinomial logit model to investigate the motivation of alternative farming adoption choices at the farm level; in the second, we apply a spatial regression analysis to examine the determinants of agglomeration in AES participation.

Therefore, we introduce two independent methodologies. The first concerns the choice model at the farm level (i.e., multinomial logit), and in the second, the spatial econometrics model is applied to aggregated participation at the municipality level.

The choice model (i.e., multinomial logit) is commonly used in the AES literature [34]. The model is particularly appropriate for empirically testing the provided theoretical model, since the decision concerns the adoption of mutually exclusive farming systems [15]. In fact,  $U_{ij}$  denotes a non-observed utility that the farm derives from the adoption of alternative farming systems ( $j$ ), with  $j = (1, 2, 3)$ . Then, it is possible to write  $U_{ij} = \mu_{ij} + \varepsilon_{ij}$ , where  $\mu_{ij}$  is an observable portion of the utility function, which is a linear combination of the covariates (set of observed variables), and  $\varepsilon_{ij}$  is an unobservable term [35].

Assuming that  $\varepsilon_{ij}$  are independent and in the form of a Gumbel distribution, the probability that the  $i$ -th farm belongs to the farming system ( $j$ ) is  $P_{ij} = \frac{\exp\{\mu_{ij}\}}{\sum_j^M \exp\{\mu_{ij}\}}$ , with  $j = 1, 2, 3$  alternatives. Under

this assumption, we automatically assume that  $0 \leq P_{ij} \leq 1$  and  $\sum_j^M P_{ij} = 1$ . Assuming that  $\mu_{ij}$  is a linear function, it would be possible to write  $x'_{ij}\beta = \mu_{ij}$ , where the matrix,  $x'_{ij}$ , contains the set of explanatory variables. Under the assumptions of linearity and a Gumbel distribution of error, it is possible to rewrite a normalized form of the probability function as follows:

$$P_{ij} = \frac{\exp\{x'_{ij}\beta\}}{\sum_j^M \exp\{x'_{ij}\beta\}} \text{ for each } j = 1, 2, 3 \text{ alternative. Thus, the probability of the } i\text{-th farmer's choice to}$$

undertake behaviour ( $j$ ) when faced with a policy change among a set of  $M$  alternatives is a function of the explanatory variables,  $x'_{ij}$ , and of the  $\beta$  coefficients [36].

Using the agglomeration effects related to AES adoption, the second applied model then allows us to describe the determinants of participation. We use a spatial econometric model to measure the share of participation in organic and integrated production in the municipalities of Tuscany. For alternative regimes, the model allows us to improve estimations of spatial associations of explanatory variables as well as the error term.

Following [37], the spatial dependency can be modelled as an extension of the standard linear regression model. We apply a general spatial model (GSM) that can be presented as follows:

$$\begin{aligned} r &= \rho W_1 r + X\beta + \varepsilon \\ \varepsilon &= \lambda W_2 \varepsilon + \mu \end{aligned} \quad (2)$$

$$E[\mu_i^2] = \sigma^2 h(z_i); E[\mu_i \mu_j] = 0 \text{ with } i \neq j,$$

where  $r$  is the vector of observed participation rates;  $X$  is the  $n \times k$  matrix of the  $k$  determinants of the participation rate;  $\beta$  are the regression parameters to be estimated;  $\varepsilon$  is the error term;  $W_1$  and  $W_2$  are the  $n \times n$  matrix of spatial weights;  $\rho$  is the spatial lag parameter; and  $\lambda$  is the spatial error coefficient. The  $i$ -th element of  $W_1 r$  represents the spatial weighted average of participation. The general model follows a specific estimation strategy on the basis of the Lagrange multiplier test. Following [38], this strategy can help suggest the worthiness of testing for correction for spatial dependence, which can take the form of an omitted spatially lagged variable (spatial lag model) or spatial autocorrelation in the disturbance term association (spatial error model), or both (GSM).

According to [39], assumptions concerning the spatial weight matrix are fundamental to the specifications of spatial phenomena; generally, they are hypothesized as being affected by neighbourhood or by distance. In the first approach, two participating municipalities (spatial units) are interrelated when they share a part of the border, while in the second approach, spatial units are interrelated on the basis of distances between centroids or some reference points. The current study uses the first-order contiguity matrix, as it is better able to capture social interaction when explaining the agglomeration of RDP participation [7,29]. The GSM simulates spatial patterns of participation in AES

while simultaneously taking into account both spatial lag and errors. While the former (i.e., spatial lag) allows us to improve the model by taking into account the effects of spatial spillovers (i.e., participation in one unit is affected by the participation of neighbouring areas, due either to an imitation process [40] or to differences in the quality of institution and extension services [41,42]), the latter allows us to improve the estimation results, including the spatial non-stationarity among observations.

#### 4. Data Used

We use 2010 census data from the Tuscany region, which are merged with ARTEA micro-level data that contain AEPs received by farmers. Both databases contain the universe of subjects—namely, Tuscan farmers who have received all ARTEA agricultural payments. ARTEA is the regional agency in charge of paying agricultural subsidies to farmers. The census database mainly contains descriptors of farm structure and farming systems, while the ARTEA database contains information on all payments, in terms of measure, scheme, and year. This latter database also contains some additional information on zoning that is used by the regional administration to set up payments for priority areas (i.e., NATURA 2000) or to apply selection or exclusion criteria (e.g., urban locations for measure 311, regarding diversification). We merged the ARTEA and census data by keying to univocal farmer ID codes, which are available in both databases. Consequently, the data inform us about both the adoption of agri-environmental prescriptions and the set of covariates that relates to farm, farmer, and household characteristics. We integrated into the dataset data concerning location, territorial description, and tourist amenities. In this section, we first introduce the data used in the farm choice model (i.e., the multinomial logit model), and then we present the data used in spatial analysis.

Tables 1 and 2 provide information on the dependent variable and explanatory variables used in the multinomial logit model.

**Table 1.** Participation in organic and integrated production.

Production System (AES)	Farmers (#)	Percentage (%)	Cumulative (%)
0 = conventional production	66,836	91.95	91.95
1 = organic production	2384	3.28	95.23
2 = integrated production	3466	4.77	100.00
Total	72,686	100.00	100.00

**Table 2.** Descriptive statistics of explanatory variables used in micro-level models.

	Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Location	rur_int (binary)	72,686	0.1009	0.3011	0	1
	rur_devprob (binary)	72,686	0.1431	0.3502	0	1
	rur_trans (binary)	72,686	0.3409	0.4740	0	1
	rur_decl (binary)	72,686	0.2413	0.4279	0	1
	urban (binary)	72,686	0.1738	0.3789	0	1
	d_natura2000 (binary)	72,686	0.3243	0.4681	0	1
Household characteristics	live_on (binary)	72,686	0.8403	0.3663	0	1
	lab_FTEall (# of full-time equivalent)	72,686	1.1225	1.6322	0	90.81
	lab_partime (binary)	72,686	0.4606	0.4984	0	1
	lab_onlyfam (binary)	72,686	0.9422	0.2334	0	1
Farm characteristics	diversification (count)	72,686	0.1279	0.4576	0	10
	prod_qual (binary)	72,686	0.1343	0.3410	0	1
	uaa_vl (binary)	72,686	0.1458	0.3529	0	1
	uaa_vs (binary)	72,686	0.4522	0.4977	0	1
	uaa1_ha (ha of UAA)	72,686	10.3781	35.0867	0	2292
	grazing_d (binary)	72,686	0.1780	0.3825	0	1
	energy_d (binary)	72,686	0.0005	0.0232	0	1
	rent_d (binary)	72,686	0.1553	0.3622	0	1



Table 2. Cont.

	Variable		Obs.	Mean	Std. Dev.	Min.	Max.
	single_plot	(binary)	72,686	0.5548	0.4970	0	1
	permanent	(binary)	72,686	0.5872	0.4923	0	1
	arable	(binary)	72,686	0.1739	0.3790	0	1
	direct_coltiv	(binary)	72,686	0.9562	0.2047	0	1
	cond_oth	(binary)	72,686	0.0060	0.0770	0	1
	herdsize	(# of livestock size unit)	72,686	1.1745	15.9962	0	1965
Farmer characteristics	internet	(binary)	72,686	0.0590	0.2357	0	1
	old	(binary)	72,686	0.4138	0.4925	0	1
	edu_agr	(binary)	72,686	0.0389	0.1933	0	1
	edu_low	(binary)	72,686	0.6697	0.4703	0	1
Policy	sfp_th	(1000s of €)	72,686	1411.35	5.7589	0	426.822
	sfp_ha	(€ per ha)	72,686	134.7563	243.4906	0	16,325

Fewer than 10% of the farms adopted integrated and organic production. More than 2000 farms adopted organic production (i.e., 3.28% of all farms), while more than 3000 farms adopted integrated production (i.e., 4.77% of all farms).

The theoretical model suggests that three main mechanisms can explain AES adoption: (a) Profitability of the new practices; (b) farmer preferences and values affecting the utility function; and (c) the level of transaction costs related to the expected mode of adoption. The literature highlights how several variables may be used as proxies of these three dimensions. Based on the aforementioned literature on the determinants of adoption—while taking into account available census data—we used the selected explanatory variables that relate to location, farmers and households, and farm policy. Table 2 presents the descriptive statistics of the selected explanatory variables, which are classified into five categories.

The first category includes RDP zoning and location with respect to NATURA 2000 areas. RDP zoning is based on inhabitant density calculated at the municipality level. Tuscany has five zones. The first of these (urban) contains farms located in urban areas (i.e., municipalities with the highest inhabitant density). The second (rur\_int) contains farms located in rural areas with an inhabitant density of fewer than 150 inhabitants per square kilometre and intensive agricultural production. Finally, the three other zones correspond to rural areas and are characterized by concerns of increasing socioeconomic relevance (i.e., rural areas in transition (rur\_trans), declining rural areas (rur\_desc), and rural areas with development problems (rur\_devprob)). The covariate, *d\_natura2000*, is a dummy variable that identifies whether a farm is located in a ‘vulnerable area’ (a NATURA 2000 or birds directive area), or in an area that is vulnerable due to excessive nitrogen. Location and altitude can affect the likelihood of observing participation in two ways. The first relates to targeting, and to the design of different payment levels [43] or the addition of a priority mechanism [7] or exclusion criteria based on localization (i.e., vulnerable zone or nitrogen-sensitive areas). The second mechanism relates to the possibility of exploiting territorial features as a part of new business opportunities [41]. This is the case when there are different demand levels for ecosystem services [44] linked to landscape or location in peri-urban areas [45].

The second category relates to explanatory variables that describe household characteristics. These variables are used to study the relationship between a farmer’s household characteristics and farming strategies used. Farm household characteristics include whether farmers live on the farm (live\_on), the relationship between a farmer’s household and external labour (lab\_FTEall; lab\_onlyfam), and the number of part-time farms (lab\_partime). These variables may be used as proxies of structural factors vis-à-vis labour availability. A large body of research notes that conservation practices and diversification [41,43] require a considerable amount of labour. In addition, whether a farmer actually lives on the farm can be used as a proxy for attitude, given the inclusion of environmental protection

in farm management (i.e., that used to enhance the long-term viability of farm tenure); it also relates to the development of a sense of belonging to a community (on this point, see [46]).

The third category of explanatory variables includes those farm characteristics that relate to the legal status of the farm (*direct\_coltiv*; *cond\_oth*), the farm's specialization (i.e., permanent, arable), farm size (dummies of quartile, *uaa\_vs*, *uaa\_s*, *uaa\_l*, and *uaa\_vl*; and the amount of operated land, *uaa1\_ha*), quality of production (*d\_quality*), and a dummy variable for single plot (*single\_plot*). These variables describe a farm's system; the characteristics behind them can affect a farmer's decision to adopt AESs, as they represent barriers or enabling factors with regard to the adoption of a new business model that differs from conventional agriculture. Many studies investigated the role of these variables in affecting mainly the profitability of conventional agriculture. For example, land availability engendered by marginal land productivity can affect the profitability scale or the economic scope, and therefore support the broadening or deepening of certain strategies [47]. Farm specialization and its legal status are largely used as main explanatory variables that act as proxies for participation costs and attitude toward changes [34].

The fourth explanatory variable category contains farmer characteristics, such as education level (*edu\_high* in the case of education higher than secondary school, *edu\_low* when farmers have education lower than secondary school, and *edu\_agr* when farmers have a professional agricultural education), and dummy variables for being 40 years or older (*old*) and using the internet for farming activities (*internet*).

The authors of [48] observe that these variables can affect the socioeconomic components of the adoption decision. In their review, [34] observe that a farmer's education level and discipline, as well as his or her age, are relevant factors that allow us to explain not only social capital, but also the possibility of earning income from other, off-farm activities. Internet use can be associated with enlarging one's business model to include opportunities to increase the provision of ecosystem services; it also associates with collecting information about implementation, and therefore with a farm's ability to reduce its transaction costs [49].

Finally, the policy category contains the single-farm payment (SFP) received for each unit of utilised agricultural area (*sfp\_ha*) or per farm (*sfp\_th*). Table 3 shows the data used in the spatial model for both dependent and explanatory variables. The inclusion of SFP allows us to explore the linkage between the first and second pillars of the CAP. The SFP shows two qualifying conditions: Payments are calculated on a historical model, and cross-compliance implies the fulfilment of compulsory norms belonging to the statutory management requirements and good agriculture and environmental practices, which are similar for all farmers. These two conditions can create a distortion, whereby farmers can receive different payment amounts, despite being subject to the fulfilment of the same prescriptions. Additionally, as compulsory norms, cross-compliances represent a baseline upon which scheme commitments are designed and the resulting payments calculated. Therefore, from a theoretical perspective, farms with higher SFPs are more likely to participate in AESs, due to the reduction in moral hazard (on this point, see [50]). However, the literature indicates the non-linear effect of first payments on AES adoption—an act that encompasses other dimensions of farm decision-making, such as investment behaviour [51,52], diversification [41], and labour allocation [53].

Individual-level census data are aggregated at the municipality level. This aggregation is performed while considering that all the farmers having headquarters in the same municipality belong to the same territorial unit. This approach has the practical consequence of allowing us to use the same information that has been used for the farm-scale analysis, but while referring to a lower number of observations (i.e., the 285 municipalities in the region) (In accordance with the agreed-upon spatial econometrics procedure [54], we excluded from the analysis the islands of the region). In Table 2, even if the same coding were maintained, the data presented in Table 3 would represent the count (c), sum (s), or average value (av) aggregated per municipality.



**Table 3.** Descriptive statistics of variables used in spatial analysis models.

	Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent variable	av_org	285	3.49	3.54	0	25
	av_int	285	4.02	4.62	0	35.71
Location and altitude	d_plain	285	0.09	0.28	0	1
	d_urban	285	0.07	0.25	0	1
	d_rur_decl	285	0.24	0.42	0	1
	d_rur_int	285	0.10	0.31	0	1
	av_natura2000	285	9.54	16.03	0	100.00
	av_NVZ	285	2.72	9.67	0	68.16
	av_park	285	6.18	13.30	0	100.00
Tourist features	s_hotel	285	166.54	223.98	0	1745.00
	s_agritourism	285	650.73	2265.16	0	30,385.00
Household	av_fteall	285	1.16	0.36	0.37	3.17
	av_ftefam	285	0.99	0.28	0.35	1.83
	av_onlyfam	285	94.06	5.73	50	100.00
Farm characteristics	av_sau	285	11.04	9.84	1.14	67.02
	av_quality	285	9.88	12.24	0	51.73
	av_diversified	285	0.17	0.18	0	1.29
	av_grapewine	285	8.19	10.63	0	53.67
	av_oliveoil	285	15.78	16.79	0	75.18
	av_forest	285	33.55	19.95	0	86.05
	av_vegetable	285	2.63	4.84	0	38.59
	av_livestock	285	6.68	7.37	0	43.75
	av_plot1	285	58.69	19.18	16.81	100.00
	av_rent	285	15.27	8.39	0	57.14
	av_owned land	285	86.02	7.27	44.24	100.00
	av_energy	285	0.02	0.13	0	1.33
	av_hedgerow	285	13.12	13.63	0	76.96
	av_arable	285	17.47	13.33	0	90.48
	av_rent	285	15.27	8.39	0	57.14
	av_soleown	285	92.51	5.56	50	100.00
	av_direcolti	285	95.09	4.83	50	100.00
av_oth_conduct	285	0.82	1.42	0	12.50	
Farmer characteristics	av_internet	285	5.95	4.46	0	38.65
	av_old	285	40.19	7.34	0	65.22
	av_farmerage	285	59.95	2.70	43.1	72.00
	av_edu_agr	285	3.65	2.82	0	23.73
Policy characteristics	s_sfp_th	285	1793.97	3000.21	0	27,900
	av_sfp_farm	285	559.57	380.99	0	3289.01
	av_sfp_ha	285	6731.70	380.98	0	3289.01

Organic and integrated production adoptions are strongly diversified across Tuscany's 285 municipalities. These two variables have values ranging from 0% (i.e., no adopters) to 25% and 35% for organic and integrated production, respectively. Municipality-level agglomeration demonstrates the importance of evaluating this phenomenon at this investigatory level rather than at a micro level, as it highlights the presence of territorial drivers otherwise ignored at the farm level. Explanatory variables are classified into the same categories as in Table 2, with the inclusion of an additional category related to tourist features. This category contains variables pertaining to the total number of hotel beds (s\_hotel) and the presence of agritourism (s\_agritourism) for each Tuscan municipality. These data were collected from the Italian National Institute of Statistics. The inclusion of these variables is motivated by the relevance of these market opportunities to farmers' decision-making processes [55].

Location variables mainly comprise dummy variables that consider RDP zoning and the share of the utilized agricultural area (UAA) of the municipalities within NATURA 2000 sites (*av\_natura2000*), nitrogen-sensitive areas (*av\_zvn*), or all protected areas, including regional protected areas (*av\_park*). The farm characteristic category contains variables that measure the share of usable agricultural land allocated to main crops (i.e., olive oil (*av\_oliveoil\_ha*), forestry (*av\_forestry*), vegetables (*av\_vegetable*), vineyards (*av\_grapewine*), and energy crops (*av\_energy*)). These variables measure the share of utilised agricultural area allocated to each crop. The variable, *av\_forestry*, measures the share with respect to the total agricultural area. Additional variables belonging to this category are the average farm size (*av\_sau*) and dummy variables that describe the land tenure characteristics of a farm in a municipality: *Av\_owner* is the share of farms whose land is owned by their respective farmers, and *av\_rent* is the share of farms rented by their farmers. In this category are variables that describe the legal status of a farm (e.g., *d\_direcolti* pertains to a farm in which more than one-third of the household labour has been allocated, and where most of the household's income derives from agriculture). Finally, there are variables that describe the typology and intensity of production; these refer to the share of farms that sell certified quality production (*av\_quality*) and to the share of farms that diversify production by allocating labour to on-farm activities other than crop cultivation and animal rearing (*av\_diversified*).

The farmer characteristics variables are enumerated as follows: (i) The average age of the land manager, (ii) the share of farmers that use the internet to buy or sell farm inputs/outputs, and (iii) the share of farmers with an agricultural education. Explanatory variables are used in both models to study the same determinants, but their spatial aggregation levels differ.

## 5. Results and Discussion

This section addresses the results of using the multinomial logit model and the spatial regression model. As discussed, both models are used to study the determinants of participation in organic and integrated production, but they estimate the determinants of AES participation in different ways.

### 5.1. Farm Choice Model Results

The multinomial logit model is used to identify determinants at the farm level, while spatial regression analysis is used to identify determinants at the territorial level. It is worthwhile to note that even if the analyses were to use the same data, the two model approaches would not necessarily return the same results, given explicit considerations of space and of the developmental status of a territory. In fact, the latter model considers determinants of agglomeration effects, rather than simple adoption. Discrepancies among the models can be a consequence of spatial spillover and the selection mechanism implemented at the territorial level, and these are not captured by the farm choice model.

Table 4 presents the results of using the farm choice model when adopting organic farming or integrated production.

The positive (negative) sign of the  $\beta$  coefficients, when significant, can be interpreted as an increase (a decrease) in the probability that a farmer with certain characteristics will adopt organic or integrated production rather than a conventional system. The analytical results confirm that being in a rural location positively affects the adoption of organic production, in areas featuring either development problems or transition. Farmers located in these areas also show a positive probability of adopting integrated production. Taken together, these results support previous findings that identify marginal areas (i.e., of low quality or bearing some natural handicap) as those with low compliance costs [20]. On the other hand, farms located in urban areas show a higher probability of adopting integrated production; this is mainly a consequence of a higher opportunity for off-farm income (note that organic farming requires more labour than integrated or conventional farming). Note that the farm characteristic variables have the same effects in explaining the probability of adopting either integrated or organic production: Specifically, the adoption of quality production and on-farm diversification positively affects the probability of observing the adoption of integrated or organic

farming systems. The results confirm a threshold effect (produced by the farm size) on the choice of participation in either measure. For small farms, transaction costs represent a barrier to participation in integrated and organic production. Different signs between determinants of organic production and those of integrated production adoption are observed when one considers specialization and farm efficiency. While participation in both measures is observed for permanent crops, farmers with areas allocated to grassland and meadow show a positive (negative) probability of partaking in organic production (integrated production). These results are consequences of high payments relative to very low compliance costs for introducing or maintaining these crops (grasslands and meadows) under an organic farming system. Otherwise, farmers with more plots are more likely to be involved in integrated production, given the higher flexibility of this measure in comparison with organic production—or, due to more opportunities to allocate production among several plots.

**Table 4.** Multinomial logit model results.

Variable	Organic Production		Integrated Production	
	Coeff.	Std. Err.	Coeff.	Std. Err.
rur_int	−0.179	0.111	−0.0626	0.0871
rur_devprob	0.144 *	0.0747	0.220 ***	0.0624
rur_trans	0.225 ***	0.0552	0.134 ***	0.0479
urban	−0.0743	0.0819	0.277 ***	0.0623
d_natura2000	0.624 ***	0.0503	0.797 ***	0.0416
diversification	0.556 ***	0.0277	0.186 ***	0.0301
prod_qual	0.654 ***	0.0513	0.297 ***	0.0457
uaa_vl	0.790 ***	0.0561	1.045 ***	0.0475
uaa_vs	−2.562 ***	0.121	−1.553 ***	0.0735
uaa1_ha	0.00362 ***	0.000435	0.00293 ***	0.000429
grazing_d	0.187 ***	0.0558	−0.117 **	0.0496
energy_d	−1.62	1.084	−0.175	0.513
rent_d	0.132 **	0.0518	0.462 ***	0.0421
single_plot	−0.173 ***	0.0487	0.394 ***	0.0448
permanent	0.357 ***	0.0566	0.271 ***	0.0485
arable	−0.507 ***	0.0744	−0.158 ***	0.0547
inform_d	0.686 ***	0.0633	0.355 ***	0.0612
old	−0.934 ***	0.0611	−0.885 ***	0.0491
edu_agr	−0.208 **	0.0878	0.147 *	0.0755
edu_low	−0.583 ***	0.0503	−0.228 ***	0.0433
live_on	0.286 ***	0.0653	0.422 ***	0.0602
lab_FTEall	−0.0802 ***	0.0123	−0.00799	0.0094
lab_parttime	−0.275 ***	0.0582	−0.657 ***	0.0513
lab_onlyfam	−0.472 ***	0.0873	−0.0542	0.0843
direct_coltiv	0.117	0.108	−0.0783	0.107
cond_oth	−0.682 **	0.281	−0.408	0.268
herdsize	0.0005	0.000776	0.0013 **	0.000586
sfpr_th	0.0053	0.0062	0.0038	0.0044
sfpr_ha	$-6.98 \times 10^{-5}$	0.00015	0.000779 ***	0.0000736
Constant	−3.080 ***	0.139	−3.798 ***	0.134
Observations		72,686		72,686
Adjusted R <sup>2</sup>			0.237	

\*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

In line with previous research findings, farmer characteristics, such as age and education, affect attitudes and skills, and they are relevant to explaining the adoption of either organic or integrated production. Young and well-educated farmers are more likely to participate in an AES programme [19]. It is noteworthy that having an agricultural education positively affects the adoption of integrated production, but negatively affects the adoption of organic production. According to [56], successful

integrated production demands a more technical education, especially when one considers the high-quality extension services available to organic farming systems.

Labour endowments and the allocation of household labour among on-farm and off-farm activities are also determinants of adoption, of either integrated or organic farming practices. Our results indicate that households living on-farm are more likely to adopt integrated or organic production, while part-time farming differentially affects adoption.

Results with respect to the linkage between first and second-pillar policies show that SFPs (i.e., income support instruments) positively affect the likelihood of AES adoption. In particular, the amount of payments received per year highlights a positive correlation with the adoption of organic and integrated production, while the intensity of payment (i.e., payments received per hectare of UAA) positively affects integrated production adoption. The economics literature identifies SFP as a main component that ameliorates credit market imperfections and consequently provides support in adopting innovative business models (e.g., organic farming and investments in equipment and tools needed for organic production). Furthermore, empirical findings show that in terms of maintaining a high level of production quality, eligible crops for SFP entitlements are mainly cereals and protein-rich and oleaginous crops that incur integrated-production compliance costs lower than those of organic production.

## 5.2. Spatial Model Results

Let us look at the spatial model results. Table 5 presents the results of tests for spatial dependency in the form of an omitted spatially lagged variable or spatial autocorrelation in the disturbance term of the shares of organic and integrated production.

**Table 5.** Spatial dependency tests of AES participation.

	Organic Production		Integrated Production	
	Statistic	<i>p</i> -Value	Statistic	<i>p</i> -Value
Moran's I	3.220	0.001	2.504	0.012
LM (spatial error)	6.328	0.018	3.100	0.078
Robust LM (spatial error)	3.231	0.072	0.320	0.576
LM (spatial lag)	0.091	0.762	8.152	0.004
Robust LM (spatial lag)	0.049	0.825	5.372	0.020

The Lagrange multiplier test results show that the nuisance dependence in the disturbance term significantly affects the distribution of the share of organic production, while the omitted spatially lagged variable affects the integrated production. The results positively support the application of spatial econometric models to improve estimations of the agglomeration effects of AES adoption. As seen in the literature, many explanatory variables could have spatial dependencies, and several elements that are not captured by the model (e.g., quality of institution, development and quality of networks) have spatial non-stationarity and could thus affect alternative performance in AES participation across several territorial areas. Then, following [38], we implement a spatial econometrics model instead of a traditional ordinary least squares (OLS) model; this allows for more robust estimation. Therefore, in accordance with [38,54], we run a spatial error model for the share of organic production and a spatial lag model for the share of integrated production. Table 6 presents the determinants of the share of adoption of organic production (model 1) and the share of adoption of integrated production (model 2) among Tuscany's municipalities.

Table 6. Results of spatial analysis models.

Variable	Organic Production (Model 1)				Integrated Production (Model 2)			
	A-Spatial (OLS)		Spatial Error Model		A-Spatial (OLS)		Spatial Lag Model	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
d_plain	−3.616 *	1.971	−3.905 *	2.019	−9.167 **	4.456	−7.431 *	4.232
av_natura2000	0.0228	0.0307	0.0266	0.0295	0.0905	0.0784	0.0788	0.0738
av_NVZ	0.0411	0.0445	0.0217	0.0456	0.610 ***	0.113	0.519 ***	0.111
av_park	−0.0734 *	0.0379	−0.0631 *	0.0374	−0.224 **	0.0956	−0.221 **	0.0898
d_urban	6.045 ***	2.05	6.600 ***	2.019	16.69 ***	4.5	15.60 ***	4.246
d_rur_decl	−2.044 **	1.019	−2.326 **	1.021	3.823	2.517	3.517	2.367
d_rur_int	1.403	1.553	1.831	1.655				
s_agritourism	0.0304 ***	0.00212	0.0304 ***	0.00204	0.0600 ***	0.00513	0.0569 ***	0.00495
s_hotel	0.00484 **	0.00188	0.00461 ***	0.00076				
av_ftefam	−2.684 *	1.522	−2.125	1.481	0.594	0.487	0.629	0.458
av_onlyfam	0.185 **	0.092	0.192 **	0.0885				
av_farmerage	0.00187	0.367	−0.0794	0.34				
d_internet					−0.303	0.295	−0.22	0.278
av_sau	0.223 **	0.0943	0.230 **	0.0911	−0.232	0.244	−0.245	0.229
av_plot1					0.156 **	0.0664	0.137 **	0.0628
d_energy_ha	−4.383	3.021	−5.102 *	2.806	−16.11 **	7.689	−17.39 **	7.238
s_totliv					0.414 **	0.177	0.414 **	0.166
av_quality	0.144 ***	0.0376	0.157 ***	0.0381				
av_diversified	−2.77	2.892	−1.458	2.822	−8.222	6.828	−5.639	6.481
s_grapewine_ha	−0.0399	0.0481	−0.0393	0.048				
av_oliveoil_ha					0.232 ***	0.0833	0.232 ***	0.0783
av_owned land	−0.0509	0.0697	−0.0305	0.0656	0.259	0.175	0.197	0.166
av_hedgerow	0.0720 **	0.0298	0.0706 **	0.0286				
av_spec_arable	−0.0895 **	0.0444	−0.0808 *	0.0425	0.302 **	0.117	0.305 ***	0.11
av_rent	0.138 *	0.0738	0.103	0.0724	0.202	0.193	0.132	0.183
av_forest_ha	0.0347	0.0269	0.0187	0.0268				
d_direcolti					−0.571	0.396	−0.501	0.373
d_oth_conduct					1.218 ***	0.393	1.129 ***	0.37
d_oth_conduct	−0.36	0.29	−0.323	0.269	1.004	0.748	0.912	0.704
d_old	0.0862	0.13	0.124	0.12				
d_edu_agr	−0.123	0.147	−0.111	0.138				
av_sfp_farm	$−5.2 \times 10^{-5}$	0.00215	−0.00017	0.0021	0.00554	0.00568	0.00412	0.00537
av_sfp_ha	$−4.8 \times 10^{-5}$	0.000129	$−5.2 \times 10^{-5}$	0.000122	−0.00011	0.000329	$−5 \times 10^{-5}$	0.00031
Lambda			0.226 **	0.0898				
Rho							0.181 ***	0.0648
Constant	−15.17	20.06	−14.41	18.92	−142.8 ***	41.73	−137.6 ***	39.26
Observations	285		285		285		285	
R <sup>2</sup>	0.664		0.689		0.515		0.5521	
Adj. R <sup>2</sup>	0.6285		0.6443		0.4699		0.5212	

\*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

For each AES considered (be it organic or integrated), model A refers to OLS, while model B refers to the GSM.

The  $R^2$  values vary between the models. Both spatial models show high  $R^2$  values, and this confirms an improvement in the estimations for both the spatial error and spatial lag models. The spatial dependence ( $\rho$ ) and spatial error coefficients ( $\lambda$ ) are significant and positive. Taken together, the significance and positive signs of both variables highlight that, inter alia, a 1% increase in the share of integrated production in one municipality will, in neighbouring municipalities, lead to an incremental increase exceeding 0.18 for organic or integrated production. Consequently, the results highlight that the agglomeration of organic production is affected by spatial autocorrelation in the disturbance term; therefore, the model suggests that the agglomeration of organic production needs to be explained by some factor not caught by the model, but which has some spatial pattern. The leading mechanisms can relate to other variables that may explain social capital or the quality of an institution—variables that, on a territorial basis, can explain the lower transaction costs associated with a conversion to organic production.

The results indicate that farm location affects adoption, and therefore the overall share of farms that adopt AESs. In particular, being located on a plain was found to have a negative effect on the expected share of organic production. Meanwhile, the share of integrated production mainly derives from spatial autocorrelation in the disturbance term, as confirmed by the non-significance of the



variable under the spatial error model. The results of the multinomial logit model show the opposite effects of this variable on AES participation: The share of integrated production is positively affected by the proportion of nitrogen-vulnerable area within a municipality, which represents a spatial priority for both measures. The positive and significant coefficient is determined by the design of integrated production measures; in fact, targeted areas are prioritized. Otherwise, zoning was not found to be a determinant of the share of organic farming. The results show that the agglomeration effects of organic adoption are driven mainly by motivation rather than by policy mechanisms. In any case, RDP zoning was found to strongly affect AES participation: Its positive effect on the share of both AES types was observed in urban areas, where there is proximity to markets.

The spatial analysis undertaken here allows for the inclusion, as an explanatory variable, of some elements of territorial endogeneity, such as tourist features or demand. Research results indicate that being rich in tourist features (measured as the number of hotel beds per municipality) increases an area's expected value with respect to AES participation. The share of organic farming also positively correlates with the development of rural tourism in the area. Consequently, the results confirm those in the literature, which assert that a high intensity of diversification can be found in tandem with organic farming—a dual approach that represents a viable farm business strategy [41]).

The spatial model results show also that both farm and farmer characteristics have a relevant role in explaining AES adoption. The results appear to support the farm choice model estimations, where household-labour endowments and legal status affect participation. In particular, the variable relating to the use of household labour positively affects organic farming adoption, while direct cultivation legal status positively affects integrated production.

Our results indicate that, with the exception of farm size—which positively increases the share of organic production and negatively affects the share of integrated production—other farm variables, such as land use, number of plots, and livestock activities, increase the expected value of integrated production.

It is noteworthy that the share of organic farming and the agglomeration of farmers who sell quality products strongly correlate. In fact, our results indicate that the value of the dummy variable of sold production under PDO (*av\_quality*) is both positive and significant. This highlights not only the fact that quality products and organic farming may share a relevant producer network, but that they might also by extension belong to the same food chain.

Our study results confirm those in the literature *vis-à-vis* substitution effects between AES and energy crops [57]. In fact, in areas where a large share of land is allocated to energy production, one sees a lower share of AES; this is a consequence of a negative and significant coefficient (*av\_energy*). The results of spatial analysis confirm the different effects of specialization in arable crops between integrated and organic farming.

## 6. Conclusions

The current study examined the determinants of agri-environmental scheme (AES) adoption. The methodology applied herein allowed the results from a farm-level model (i.e., a multinomial logit model) and a territory-level model (i.e., spatial econometric analysis) to be compared, and thus derive possible interpretations. The dependent and covariate variables referenced the same dataset, but with different spatial aggregations. The multinomial logit model analysed, at the farm level, the determinants of organic or integrated production adoption, while spatial econometric analysis looked at the agglomeration effects of participation in organic or integrated production in Tuscany's municipalities.

The model results are consistent in explaining the determinants of integrated and organic production adoption, and by comparing those results, it is possible to obtain a better understanding of the AES participation mechanism. The results align with previous findings, in that they identified farm, farmers, location, and household characteristics as the main determinants in explaining multifunctional adoption practices among new production models.

We used the aforementioned models to investigate the determinants of organic farming adoption under an AES; however, not all organic farmers participate in AESs, and many of them sell organic products without being involved in one. The main reasons for this lack of participation are the high transaction costs associated with AES participation, and the lack of flexibility that farmers face when implementing AES practices. Thus, our results centred only on AES participation, and determinants were investigated only for the farmers studied. This consideration has some practical implications vis-à-vis AES design. In fact, many farmers will continue to adopt organic production even in cases where payments are discontinued, given motivational elements that relate to networking and social capital. Our results align with previous findings regarding morality-based motivations for engaging in organic farming [56,58]; those findings indicate potential 'deadweight' in measures' implementation, compared with integrated production.

Our findings from both models suggest that the adoption of organic farming is more strongly affected by motivational, information-based, and networking elements than it is by integrated production. As a result, the agglomeration of organic production is less sensitive to the priority mechanisms implemented by local administrators than to spatial agglomeration, the latter of which follows other spatial regimes that are perhaps linked to institution quality and social capital. The development of better policy targets is a central issue in designing and implementing rural development policy programmes. Particularly for environmental objectives, spatial agglomeration and spatial concentration in the target areas are key factors with which to assess program effectiveness. Nonetheless, research results show that priority mechanisms or selection criteria implemented by local administrators have had no effect in determining a desirable spatial distribution of participation in organic farming. To enhance participation in a targeted area, it might be useful to develop collective participation, so as to improve networking and social capital and information flows among farmers [45].

The economics literature documents a strong linkage between the two pillars and which affects farmers' decision-making [41] and their territorial transitions [10,59] towards multifunctionality. In fact, both the first and second pillars maintain viable farming and agricultural profitability and can therefore contribute to investments in agriculture and to the adoption of environmentally friendly management systems. From a theoretical perspective, the inclusion of cross-compliance as an AES baseline should rationalize the farm choice and would in turn support higher adoption rates and lower participation costs overall. The results highlight the fact that there is a weak connection between first and second-pillar policies. In combining the two models, we observed something rather puzzling about the first pillar, in how it affects AES participation. In fact, our model results failed to confirm such linkages: Only the adoption of integrated production was positively affected by first-pillar payments. This finding is perhaps supported by those of previous studies that highlight the low effectiveness of common agricultural policy payments in affecting transitions towards sustainable agricultural practices [60]; this low effectiveness may be due to low levels of commitment to cross-compliance, or to information asymmetry [9] or to strategic behaviour [50]. This relationship should be strengthened by the inclusion of 'greening', which speaks to additional green commitments and in turn additional SFP payments; it also serves as an additional AES baseline. Although there were high hopes attached to the implementation of greening [60]—especially among non-profit organizations (NGOs) and other environmental associations—ex post evaluations of greening have shown it to have made limited contributions to improved environmental quality in rural areas. Our results align with this finding and show that first-pillar payments do not effectively contribute to AES agglomeration—and, therefore, that it offers only limited environmental benefits. A further strengthening of such linkages could perhaps be created by implementing different cross-compliance commitments, with the aim of promoting farmer engagement with local institutions or with local advice-system centres. Such actions could enhance the social capital of farms or create a community of practices that looks to share experiences and best practices. In this way, these actions could contribute to mutual learning or to reductions in the transaction costs that relate to sustainable practices adoption.

We sought to achieve a better understanding of the determinants of AES adoption and agglomeration. To do so, we combined two different approaches: One that investigated micro-level (i.e., farm-level) determinants, and another that investigated those at the meso level (i.e., municipality level). Despite our finding that the interplays between these two levels of analyses constitute a relevant area of interaction, they have received scant attention in the academic literature. Leveraging this enhanced understanding can usher in a more widespread transition toward more sustainable farming practices. Other related areas of research could involve micro-level choice modelling while examining spatial patterns (e.g., looking at the distances to markets). Alternatively, future research could look at the effects of proximity to nearby institutions, or group effects on account of belonging to the same area (e.g., [43]).

**Author Contributions:** Conceptualization, F.B.; Methodology, and Formal Analysis, D.V.; Writing-Original Draft Preparation, F.B. and D.V.; Writing-Review & Editing, F.B. and D.V.; Supervision, F.B.

**Funding:** This research received no external funding.

**Acknowledgments:** The paper is based on an earlier version prepared for presentation at the 53rd ERS conference. “Regional integration: Europe, the Mediterranean and the World economy” 27–31 August 2013 Palermo.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. European Commission. *Technical Elements of Agri-Environment-Climate Measure in the Programming Period 2014–2020*; Draft 7 May 2013; European Commission: Brussels, Belgium, 2014.
2. Uthes, S.; Matzdorf, B. Studies on Agri-environmental Measures: A Survey of the Literature. *Environ. Manag.* **2013**, *51*, 251–266. [[CrossRef](#)] [[PubMed](#)]
3. Chabé-Ferret, S.; Subervie, J. How much green for the buck? Estimating additional and windfall effects of French agro-environmental schemes by DID-matching. *J. Environ. Econ. Manag.* **2013**, *65*, 12–27. [[CrossRef](#)]
4. Arata, L.; Sckokai, P. *The Impact of Agri-environmental Schemes on Farm Performance in Five E.U. Member States: A DID-Matching Approach, Land Economics*; University of Wisconsin Press: Madison, WI, USA, 2016; Volume 92, pp. 167–186.
5. D’Alberto, R.; Zavalloni, M.; Raggi, M.; Viaggi, D. AES Impact Evaluation with Integrated Farm Data: Combining Statistical Matching and Propensity Score Matching. *Sustainability* **2018**, *10*, 4320. [[CrossRef](#)]
6. Viaggi, D.; Raggi, M.; Gallerani, V. Evaluating the potential contribution of contract auctions to Agri-Environmental Policy efficiency: A simulation model for Emilia-Romagna (Italy). *Agric. Econ. Res. Rev.* **2008**, *11*, 18–28.
7. Raggi, M.; Viaggi, D.; Bartolini, F.; Furlan, A. The role of policy priorities and targeting in the spatial location of participation in Agri-Environmental Schemes in Emilia-Romagna (Italy). *Land Use Policy* **2015**, *47*, 78–89. [[CrossRef](#)]
8. Finn, J.A.; Bartolini, F.; Bourke, D.; Kurz, I.; Viaggi, D. Ex post environmental evaluation of agri-environment schemes using experts’ judgements and multicriteria analysis. *J. Environ. Plan. Manag.* **2009**, *52*, 717–737. [[CrossRef](#)]
9. Vergamini, D.; Viaggi, D.; Raggi, M. Integrating spatial econometric information and optimisation models to improve agri-Environmental payment design: A resource allocation model for emilia-Romagna (Italy). *Agric. Econ. Rev.* **2017**, *18*, 40–59.
10. Boncinelli, F.; Bartolini, F.; Brunori, G.; Casini, L. Spatial analysis of the participation in agri-environment measures for organic farming. *Renew. Agric. Food Syst.* **2016**, *31*, 375–386. [[CrossRef](#)]
11. Arnott, D.; Chadwick, D.; Harris, I.; Koj, A.; Jones, D.L. What can management option uptake tell us about ecosystem services delivery through agri-environment schemes? *Land Use Policy* **2019**, *81*, 194–208. [[CrossRef](#)]
12. Uthes, S.; Matzdorf, B.; Müller, K.; Kaechele, H. Spatial Targeting of Agri-Environmental Measures: Cost-Effectiveness and Distributional Consequences. *Environ. Manag.* **2010**, *46*, 494–509. [[CrossRef](#)]
13. Wünscher, T.; Engel, S.; Wunder, S. Spatial targeting of payments for environmental services: A tool for boosting conservation benefits. *Ecol. Econ.* **2008**, *65*, 822–833. [[CrossRef](#)]

14. Wätzold, F.; Drechsler, M. Spatially Uniform versus Spatially Heterogeneous Compensation Payments for Biodiversity-Enhancing Land-Use Measures. *Environ. Resour. Econ.* **2005**, *31*, 73–93. [[CrossRef](#)]
15. Jongeneel, R.A.; Polman, N.B.; Slangen, L.H. Why are Dutch farmers going multifunctional? *Land Use Policy* **2008**, *25*, 81–94. [[CrossRef](#)]
16. Regione Toscana. Le misure agroambientali. In *Valutazione in Itinere, Intermedia ed ex Post del PSR 2007-2013 della Regione Toscana*; Lattanzio: Firenze, Italy, 2014; p. 122.
17. Morris, C.; Potter, C. Recruiting the New Conservationists: Farmers' Adoption of Agri-environmental Schemes in the U.K. *J. Rural Stud.* **1995**, *11*, 51–63. [[CrossRef](#)]
18. Wilson, G.A. From productivism to post-productivism ... and back again? Exploring the (un)changed natural and mental landscapes of European agriculture. *Trans. Inst. Br. Geogr.* **2001**, *26*, 77–102. [[CrossRef](#)]
19. Drake, L.; Bergstrom, P.; Svedsater, H. Farmers' attitudes and uptake. In *Countryside Stewardship: Farmers*; Van Huylenbroeck, G., Whitby, M., Eds.; Policies and Markets Elsevier Science: Oxford, UK, 1999; pp. 89–111.
20. Defrancesco, E.; Gatto, P.; Runge, F.; Trestini, S. Factors Affecting Farmers' Participation in Agri-environmental Measures: A Northern Italian Perspective. *J. Agric. Econ.* **2008**, *59*, 114–131. [[CrossRef](#)]
21. Ridier, A. Farm Level Supply of Short Rotation Woody Crops: Economic Assessment in the Long-Term for Household Farming Systems. *Can. J. Agric. Econ.* **2012**, *60*, 357–375. [[CrossRef](#)]
22. Mettepenningen, E.; Verspecht, A.; Van Huylenbroeck, G. Measuring private transaction costs of European agri-environmental schemes. *J. Environ. Plan. Manag.* **2009**, *52*, 649–667. [[CrossRef](#)]
23. Giovanopoulou, E.; Nastis, S.A.; Papanagiotou, E. Modeling farmer participation in agri-environmental nitrate pollution reducing schemes. *Ecol. Econ.* **2011**, *70*, 2175–2180. [[CrossRef](#)]
24. Dupraz, P.; Latouche, K.; Turpin, N. Threshold effect and co-ordination of agri-environmental efforts. *J. Environ. Plan. Manag.* **2009**, *52*, 613–630. [[CrossRef](#)]
25. Ducos, G.; Dupraz, P.; Bonnieux, F. Agri-environment contract adoption under fixed and variable compliance costs. *J. Environ. Plan. Manag.* **2009**, *52*, 669–687. [[CrossRef](#)]
26. Espinosa-Goded, M.; Barreiro-Hurlé, J.; Ruto, E. What do farmers want from agri-environmental scheme design? A choice experiment approach. *J. Agric. Econ.* **2010**, *61*, 259–273. [[CrossRef](#)]
27. Baumgart-Getz, A.; Prokopy, L.S.; Floress, K. Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. *J. Environ. Manag.* **2012**, *96*, 17–25. [[CrossRef](#)] [[PubMed](#)]
28. Bartolini, F.; Raggi, M.; Viaggi, D. A spatial analysis of participation in RDP measures: A case study in Emilia Romagna Region. In Proceedings of the 1st AIEAA (Associazione Italiana Di Economia Agraria E Applicata) Conference "Towards a Sustainable Bio-economy: Economic Issues and Policy Challenges", Italy, Trento, 4–5 June 2012.
29. Schmidtner, E.; Lippert, C.; Engler, B.; Haring, A.M.; Aurbacher, J.; Dabbert, S. Spatial distribution of organic farming in Germany: Does neighbourhood matter? *Eur. Rev. Agric. Econ.* **2012**, *39*, 661–683. [[CrossRef](#)]
30. Wollni, M.; Andersson, C. Spatial patterns of organic agriculture adoption: Evidence from Honduras. *Ecol. Econ.* **2014**, *97*, 120–128. [[CrossRef](#)]
31. Piorr, A.; Viaggi, D. The spatial dimension of Public Payments for Rural Development: Evidence on allocation practices, impact mechanisms, CMEF indicators, and scope for improvement. *Ecol. Indic.* **2015**, *59*, 1–5. [[CrossRef](#)]
32. Gava, O.; Favilli, E.; Bartolini, F.; Brunori, G. Knowledge networks and their role in shaping the relations within the Agricultural Knowledge and Innovation System in the agroenergy sector. The case of biogas in Tuscany (Italy). *J. Rural Stud.* **2017**, *56*, 100–113. [[CrossRef](#)]
33. Boncinelli, F.; Bartolini, F.; Casini, L.; Brunori, G. On farm non-agricultural activities: Geographical determinants of diversification and intensification strategy. *Let. Spat. Resour. Sci.* **2017**, *10*, 17–29. [[CrossRef](#)]
34. Lastra-Bravo, X.B.; Hubbard, C.; Garrod, G.; Tolón-Becerra, A. What drives farmers' participation in EU agri-environmental schemes?: Results from a qualitative meta-analysis. *Environ. Sci. Policy* **2015**, *54*, 1–9. [[CrossRef](#)]
35. Werbeek, M. *A Guide to Modern Econometrics*; John Wiley & Sons: Hoboken, NJ, USA, 2004.
36. Green, W. *Econometric Analysis*; Prentice Hall Inc.: Upper Saddle River, NJ, USA, 2000.
37. LeSage, J.P.; Pace, R.K. *Introduction to Spatial Econometrics*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2009.
38. Anselin, L. Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity. *Geogr. Anal.* **1988**, *20*, 1–17. [[CrossRef](#)]

39. Corrado, L.; Fingleton, B. Where is the economics in Spatial Econometrics? *J. Reg. Sci.* **2012**, *52*, 210–239. [[CrossRef](#)]
40. Läpple, D.; Rensburg, T.V. Adoption of organic farming: Are there differences between early and late adoption? *Ecol. Econ.* **2011**, *70*, 1406–1414. [[CrossRef](#)]
41. Bartolini, F.; Andreoli, M.; Brunori, G. Explaining determinants of the on-farm diversification: Empirical evidence from Tuscany region. *Bio Based Appl. Econ.* **2014**, *3*. [[CrossRef](#)]
42. Yang, A.L.; Rounsevell, M.D.A.; Wilson, R.M.; Haggett, C. Spatial analysis of agri-environmental policy uptake and expenditure in Scotland. *J. Environ. Manag.* **2014**, *133*, 104–115. [[CrossRef](#)] [[PubMed](#)]
43. Boncinelli, F.; Bartolini, F.; Casini, L. Structural factors of labour allocation for farm diversification activities. *Land Use Policy* **2018**, *71*, 204–212. [[CrossRef](#)]
44. Wolff, S.; Schulp, C.J.E.; Verburg, P.H. Mapping ecosystem services demand: A review of current research and future perspectives. *Ecol. Indic.* **2015**, *55*, 159–171. [[CrossRef](#)]
45. Zavalloni, M.; Raggi, M.; Viaggi, D. Agri-environmental policies and public goods: An assessment of coalition incentives. *Environ. Resour. Econ.* **2018**. [[CrossRef](#)]
46. de Krom, M.P. Farmer participation in agri-environmental schemes: Regionalisation and the role of bridging social capital. *Land Use Policy* **2017**, *60*, 352–361. [[CrossRef](#)]
47. Van der Ploeg, J.D.; Renting, H. Behind the ‘redux’: A rejoinder to David Goodman. *Sociol. Rural.* **2004**, *44*, 234–242. [[CrossRef](#)]
48. Gatto, P.; Mozzato, D.; Defrancesco, E. Analysing the role of factors affecting farmers’ decisions to continue with agri-environmental schemes from a temporal perspective. *Environ. Sci. Policy* **2019**, *92*, 237–244. [[CrossRef](#)]
49. Mozzato, D.; Gatto, P.; Defrancesco, E.; Bortolini, L.; Pirotti, F.; Pisani, E.; Sartori, L. The role of factors affecting the adoption of environmentally friendly farming practices: Can geographical context and time explain the differences emerging from literature? *Sustainability* **2018**, *10*, 3101. [[CrossRef](#)]
50. Bartolini, F.; Gallerani, V.; Raggi, M.; Viaggi, D. Modelling the linkages between cross-compliance and agri-environmental schemes under asymmetric information. *J. Agric. Econ.* **2012**, *63*, 310–330. [[CrossRef](#)]
51. Viaggi, D.; Raggi, M.; Gomez y Paloma, S. Farm-household investment behaviour and the CAP decoupling: Methodological issues in assessing policy impacts. *J. Policy Model.* **2011**, *33*, 127–145. [[CrossRef](#)]
52. Bartolini, F.; Viaggi, D. The common agricultural policy and the determinants of changes in EU farm size. *Land Use Policy* **2013**, *31*, 126–135. [[CrossRef](#)]
53. Olper, A.; Raimondi, V.; Cavicchioli, D.; Vigani, M. Do CAP payments reduce farm labour migration? A panel data analysis across EU regions. *Eur. Rev. Agric. Econ.* **2014**, *41*, 843–873. [[CrossRef](#)]
54. Anselin, L. Spatial Econometrics. In *A Companion to Theoretical Econometrics*; Baltagi, B.H., Ed.; Blackwell Publishing Ltd.: Hoboken, NJ, USA, 2007. [[CrossRef](#)]
55. Chang, H.H.; Mishra, A.K.; Lee, T.H. A supply-side analysis of agritourism: Evidence from farm-level agriculture census data in Taiwan. *Aust. J. Agric. Resour. Econ.* **2019**. [[CrossRef](#)]
56. Mzoughi, N. Farmers adoption of integrated crop protection and organic farming: Do moral and social concerns matter? *Ecol. Econ.* **2011**, *70*, 1536–1545. [[CrossRef](#)]
57. Bartolini, F.; Gava, O.; Brunori, G. Biogas and EU’s 2020 targets: Evidence from a regional case study in Italy. *Energy Policy* **2017**, *109*, 510–519. [[CrossRef](#)]
58. Läpple, D.; Kelley, H. Understanding the uptake of organic farming: Accounting for heterogeneities among Irish farmers. *Ecol. Econ.* **2013**, *88*, 11–19. [[CrossRef](#)]
59. Zasada, I. Multifunctional peri-urban agriculture—A review of societal demands and the provision of goods and services by farming. *Land Use Policy* **2011**, *28*, 639–648. [[CrossRef](#)]
60. Pe’er, G.; Dicks, L.V.; Visconti, P.; Arlettaz, R.; Báldi, A.; Benton, T.G.; Henle, K. EU agricultural reform fails on biodiversity. *Science* **2014**, *344*, 1090–1092. [[CrossRef](#)] [[PubMed](#)]

